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A note on the U, V method of estimation*

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Abstract: The U, V method of estimation provides unbiased estimators or predictors of random quantities. The method was introduced by Robbins [3] and subsequently studied in a series of papers by Robbins and Zhang. (See Zhang [5].) Practical applications of the method are featured in these papers. We demonstrate that for one U function (one for which there is an important application) the V estimator is inadmissible for a wide class of loss functions. For another important U function the V estimator is admissible for the squared error loss function.

1. Introduction

The U, V method of estimation was introduced by Robbins [3]. The method applies to estimating random quantities in an unbiased way, where unbiasedness is defined as follows: The expected value of the estimator equals the expected value of the random quantity to be estimated. More specifically, suppose X_j, $j = 1, \ldots, n$, are random variables whose density (or mass) function is denoted by $f_{X_i}(x_i|\theta_i)$. In this paper we consider estimands of the form

$$S(\boldsymbol{X}, \boldsymbol{\theta}) = \sum_{j=1}^{n} U^*(X_j, \theta_j), \tag{1.1}$$

where $\boldsymbol{X} = (X_1, \ldots, X_n)'$ and $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_n)'$. An estimator, $V(\boldsymbol{X})$ is an unbiased estimator of S if

$$E_{\boldsymbol{\theta}} V(\boldsymbol{X}) = E_{\boldsymbol{\theta}}(S(\boldsymbol{X}, \boldsymbol{\theta})). \tag{1.2}$$

Of particular interest in applications are estimands of the form $U^*(X_j, \theta_j) = U(X_j)\theta_j$, where $U(\cdot)$ is an indicator function. Robbins [3] offers a number of examples of unbiased estimators using the U, V method. Zhang [5] studies the U, V method for estimating S and provides conditions under which the "U, V" estimators are asymptotically efficient. Zhang [5] then presents a Poisson example that deals with a practical problem involving motor vehicle accidents.

In this note we demonstrate that for many practical applications the U, V estimators are inadmissible for many sensible loss functions. In particular, for the Poisson example given in Zhang [5], for the U function given, the V estimator is inadmissible for any reasonable loss function, since the estimator is positive for some $\boldsymbol{X}$ when $S = 0$ no matter which θ is true.

Previously, Sackrowitz and Samuel-Cahn [4] showed that the U, V estimator of the selected mean of two independent negative exponential distributions is inadmissible for squared error loss.

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In the next section we examine examples in which S functions based on simple U functions are estimated by inadmissible V functions. For other simple U functions the resulting V estimators are admissible for squared error loss. These later results will be presented in Section 3.

2. Inadmissibility results

Let X_j, $j = 1, \ldots, n$, be independent random variables with density $f_{X_i}(x_i|\theta_i)$. Let $U^*(X_j, \theta_j) = U(X_j)\theta_j$, where, for some fixed $A \geq 0$,

$$U(X_j) = \begin{cases} 1, \text{ if } X_j \leq A, \\ 0, \text{ if } X_j > A. \end{cases} \tag{2.1}$$

Consider the following four distributions for X_j.

$$\text{Poisson} \quad f_X(x|\theta) = e^{-\theta}\theta^x/x! \quad (\theta > 0, x = 0, 1, \ldots), \tag{2.2}$$

$$\text{Geometric} \quad f_X(x|\theta) = (1-\theta)\theta^x \quad (0 < \theta < 1, x = 0, 1, \ldots), \tag{2.3}$$

$$\text{Exponential} \quad f_X(x|\theta) = (1/\theta)e^{-x/\theta} \quad (\theta > 0, x > 0), \tag{2.4}$$

$$\text{Uniform Scale} \quad f_X(x|\theta) = 1/\theta \quad (0 < x < \theta, \theta > 0). \tag{2.5}$$

Let $W(t)$, $t \geq 0$ be a function with the property that $W(0) = 0$ and $W(t) > 0$ for $t > 0$. Consider loss functions

$$W(a, S) = W(a - S), \tag{2.6}$$

for action a.

For the distributions in (2.2), (2.3), (2.4), (2.5), Robbins [3] finds unique unbiased estimators $V(X_j)$ for $U(X_j)\theta_j$.

Theorem 2.1. *Let X_j, $j = 1, \ldots, n$, be independent random variables whose distribution is (2.2) or (2.3) or (2.4) or (2.5). Consider the loss function given in (2.6). Let $U(X_j)$ be as in (2.1). Then the unbiased estimator $V(\boldsymbol{X}) = \sum_{j=1}^n V(X_j)$, where $V(X_j)$ is the unbiased estimator of $U(X_j)\theta_j$, is inadmissible for S given in (1.1).*

Proof. The idea of the proof is easily seen if $n = 1$. However for $n > 1$ it is instructive to see how much improvement can be made. The proof for $n = 1$ goes as follows: Let X_1 be X and θ_1 be θ. The $V(X)$ estimators for the four cases are given in Robbins [3]. For the Poisson case $V(X) = U(X-1)X$ $(V(0) = 0)$. Now let $[A]$ denote the largest integer in A less that A. Then $V([A]+1) = [A]+1$, whereas $S = U([A]+1)\theta = 0$.

If

$$V^*(X) = \begin{cases} V(X), \text{ all } X \text{ except } X = [A]+1, \\ 0, \qquad X = [A]+1, \end{cases}$$

then clearly $V^*(X)$ is better than $V(X)$ since $W(V^*([A]+1) - S) = 0$ for V^* and $W(([A]+1) - S) > 0$ for V. For the case of arbitrary n, $S = 0$ whenever all $X_j \geq ([A]+1)$ whereas $V(X) \neq 0$ whenever at least one $X_j = ([A]+1)$. If all $X_j = ([A]+1)$, then $V = n([A]+1)$. Clearly if $V^* = 0$ at such $\boldsymbol{X}$, V^* is better than V.

For the geometric distribution when $n = 1$, $V(X) = \sum_{i=0}^{X-1} U(i)$ $(V(0) = 0)$. Note $S = 0$ for $X \geq [A]+1$ but $V = [A]+1$ for all such X. Again if $V^* = V$ for $X \leq [A]$ and $V^* = 0$ for $X \geq [A]+1$, V^* is better than V. The case of arbitrary

TABLE 1
Improvement in risk for squared error loss function

A \ n	1	2	3	4	5	6	7	8	9	10
1	1.083	1.872	2.190	2.148	1.902	1.575	1.243	0.947	0.701	0.508
3	3.126	4.763	5.086	4.626	3.831	2.982	2.220	1.599	1.122	0.771
5	5.782	8.268	8.419	7.364	5.894	4.447	3.216	2.253	1.539	1.031
7	8.934	12.268	12.113	10.328	8.083	5.976	4.242	2.919	1.961	1.292
9	12.511	16.694	16.120	13.490	10.388	7.568	5.299	3.600	2.389	1.556

n is even more dramatic than is the Poisson case with $S = 0$ if all $X_j \geq [A] + 1$ whereas $V \neq 0$ on such points.

For the exponential distribution when $n = 1$, $V(X) = \int_0^X U(t)dt = X$ if $X \leq A$, and $V(X) = A$ if $X > A$. For arbitrary n, $S = 0$ whenever all $X_j > A$, whereas $V(\boldsymbol{X}) \neq 0$ on such points.

For the scale parameter of a uniform distribution with $n = 1$, $V(X) = XU(X) + \int_0^X U(t)dt$ which becomes $2X$ if $X \leq A$ and A if $X > A$. Hence as in the previous case, for arbitrary n, $S = 0$ whenever all $X_j > A$ whereas $V(\boldsymbol{X}) \neq 0$ on such points. This completes the proof of the theorem. $\square$

Remark 2.1. *Theorem 2.1 applies to the Poisson example in Zhang [5].*

Remark 2.2. *If the loss function in (2.6) is squared error then the amount of improvement in risk of V^* over V depends on n, A, and $\boldsymbol{\theta}$. It can be easily calculated. For the case where all the components of $\boldsymbol{\theta}$ are equal and each θ_i, $i = 1, \ldots, n$ is set equal to $[A] + 1$ the amount of improvement is equal to*

$$\frac{\sum_{i=1}^n \big(i([A]+1)\big)^2 C_i^n e^{-([A]+1)}([A]+1)^{[A]+1}}{([A]+1)!} \cdot \left(\frac{1 - \sum_{y=0}^{[A]+1} e^{-([A]+1)}([A]+1)^y}{y!}\right) \tag{2.7}$$

Table 1 offers the amount of improvement for $n = 1(1)10$ and for values of $A = 1, 3, 5, 7, 9$. We observe as n gets large the amount of improvement becomes smaller. Also for small n as A gets large, improvement gets large. Such observations are consistent with the asymptotic efficiency of the U, V estimator as $n \to \infty$ and with Sterling's formula.

Remark 2.3. *Theorem 2.1 also holds for predicting*

$$S^* = \sum_{j=1}^n Y_j U(X_j),$$

where Y_j has the same distribution of X_j but is unobserved.

3. Admissibility results

In this section we consider the case

$$U(X_j) = \begin{cases} 0, \text{if } X_j \leq A, \\ 1, \text{if } X_j > A, \end{cases} \quad A \geq 0;\ j = 1, \ldots, n. \tag{3.1}$$

Also we consider a squared error loss function.

Theorem 3.1. *Suppose X_j are independent with Poisson distributions with parameter λ_j. Then $V(\boldsymbol{X})$ is an admissible estimator of $S(\boldsymbol{X}, \boldsymbol{\lambda})$ for squared error loss.*

Proof. Let $n = 1$ and recall $V(X_1) = U(X_1 - 1)X_1$, $V(0) = 0$. Then

$$V(X) = \begin{cases} 0, & \text{for } X_1 = 0, 1, \dots, [A] + 1, \\ X_1, & \text{for } X_1 > [A] + 1, \end{cases}$$

while

$$U^*(X_1, \lambda_1) = U(X_1)\lambda_1 = \begin{cases} 0, & X_1 \le [A], \\ \lambda_1, & X_1 \ge [A] + 1 \end{cases}$$

Since $U^*(X_1, \lambda_1) = 0$ for $X_1 \le [A]$, any admissible estimator of $U^*(X_1, \lambda_1)$ must estimate 0 for $X_1 \le [A]$ as $V(X_1)$ does. □

At this point we can restrict the class of estimators to all those which estimate by the value 0 for all $X_1 \le [A]$. For $[X_1] \ge [A] + 1$, $U^*(X_1, \lambda_1) = \lambda_1$ and we have a traditional problem of estimating a parameter λ_1. Now we can refer to the proof of Lemma 5.2 of Brown and Farrell [1] to conclude that any estimator that can beat $V(X)$ would have to estimate 0 at $X_1 = [A] + 1$. Furthermore for the conditional problem given $X_1 > [A] + 1$, it follows by results in Johnstone [2] that X_1 is an admissible estimator of λ_1.

For arbitrary n the proof is more detailed. We give the details for $n = 2$. The extension for arbitrary n will follow the steps for $n = 2$ and employ induction. For $n = 2$, suppose $V(X_1) + V(X_2)$ is inadmissible. Then there exists $\delta^*(X_1, X_2)$ such that

$$\sum_{x_1=0}^{\infty} \sum_{x_2=0}^{\infty} \big(V(x_1) + V(x_2) - U(x_1)\lambda_1 - U(x_2)\lambda_2\big)^2 \lambda_1^{x_1} \lambda_2^{x_2} e^{-\lambda_1 - \lambda_2} / x_1! x_2!$$

$$\text{(3.2)} \ge \sum_{x_1=0}^{\infty} \sum_{x_2=0}^{\infty} \big(\delta^*(x_1, x_2) - U(x_1)\lambda_1 - U(x_2)\lambda_2\big)^2 \lambda_1^{x_1} \lambda_2^{x_2} e^{-\lambda_1 - \lambda_2} / x_1! x_2!$$

for all $\lambda_1 > 0,\ \lambda_2 > 0$, with strict inequality for some λ_1 and λ_2.

Now let $\lambda_2 \to 0$. Then by continuity of the risk function, (3.2) leads to

$$E\Big\{\big(V(X_1) - U(X_1)\lambda_1\big)^2\Big\} \ge E\Big\{\big(\delta^*(X_1, 0) - U(X_1)\lambda_1\big)^2\Big\}. \tag{3.3}$$

Since $V(X_1)$ is admissible for $U(X_1)\lambda_1$, the case $n = 1$, (3.3) implies that $V(X_1) = \delta^*(X_1, 0)$. At this point we do as in Brown and Farrell [1] by dividing both sides of (3.2) by λ_2. Reconsider (3.2) but now we can let the sum on x_2 run from 1 to ∞ since $V(X_1) = \delta^*(X_1, 0)$. Again let $\lambda_2 \to 0$ and this leads to $V(X_1) = \delta^*(X_1, 1)$. Repeat the process for $X_2 = 0, 1, \dots, [A] + 1$. Furthermore by symmetry $V(X_2) = \delta^*(0, X_2) = \cdots = \delta^*([A] + 1, X_2)$. Thus $V(X_1) + V(X_2) = \delta^*(X_1, X_2)$ on all sample points except the set $B = (X_1 \ge [A] + 2, X_2 \ge [A] + 2)$. Here $V(X_1) + V(X_2) = X_1 + X_2$ and $S = \lambda_1 + \lambda_2$. We consider the conditional problem of estimating $\lambda_1 + \lambda_2$ by $X_1 + X_2$ given $\boldsymbol{X} \in B$. Clearly when $\lambda_1 = \lambda_2 = \lambda$ no estimator can match, much less beat the risk of $X_1 + X_2$ for this conditional problem since $X_1 + X_2$ is a sufficient statistic, the loss is squared error, and $X_1 + X_2$ is an admissible estimator of 2λ. Thus $\delta^*(X_1, X_2) = V(X_1) + V(X_2)$ on the entire sample space proving the theorem.

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